

AUBE '01

12TH INTERNATIONAL CONFERENCE ^{ON} AUTOMATIC FIRE DETECTION

March 25 - 28, 2001
National Institute Of Standards and Technology
Gaithersburg, Maryland U.S.A.

PROCEEDINGS

Editors: Kellie Beall, William Grosshandler and Heinz Luck



NIST
National Institute of Standards and Technology
Technology Administration, U.S. Department of Commerce

Milan Dj. Blagojevich, Ph.D. Candidate, Dejan M. Petkovich, Ph.D., prof.,
Djordje Simich, Ph.D., prof.
Faculty of Occupational Safety, Department of Fire Protection, Nish, Yugoslavia
e-mail: milan@znrfak.znrfak.ni.ac.yu

A new algorithm for adaptive alarm threshold in fire detection system

ABSTRACT

A basic approach in adaptive modeling of any data acquisition is based on the comparison of real time data with the data previously predicted from the adequate numerical model. In this paper we suggest the time sliding window principle, the length of which is variable in real time and depends on the calculated error. Due to equal time distance in data acquisition in fire detection systems, the number of acquired data and the length time sliding window are linearly interdependent. This approach demands that the borders of time sliding window vary in real time simultaneously with the window. This approach also leads to the best fit between real time and the predicted data when the difference between those two time series of data is used as a feedback.

Generally, the source of false alarms is the application of the fixed alarm threshold decision. This can be overcome using the method of the adaptive threshold. The decision method based on an adaptive threshold employs a threshold changing in time according to the values of the input data and a fixed threshold. The aim of this paper is to introduce the method for controlling fire detection systems in adaptive sense, based on the approximation of the signal with a suitable function.

INTRODUCTION AND BACKGROUND

The major characteristic of most known algorithms for treatment of alarm is based on a fixed value of alarm threshold. The decision that was made in such a way means that this decision is based on default (defined by the standard) value. However, selection of

adequate alarm threshold is not easy, because of the noise present during data acquisition, other disturbances or uncertainty. The selection of alarm threshold is subject to permanent compromise between the low rate of false alarming with small sensitivity to failure on the one hand, and the high rate of false alarming with high sensitivity on the other hand. This conventional logic practically leads to a discrete function which from the given set of data gives one predicted output value. The adaptive alarm threshold is based on the "history" of acquired data, usually known as time series. Unfortunately, when all of data are known, the fire is fully developed, and no prediction has any sense. The prediction of fire alarm has to be stated on the arbitrary set of previous, acquired data, the fewer of them the better. If we choose to view the set of data in the time window the length of which is constant, consequently we define time sliding window with constant length. Because of the nature of the process this window must have variable length.

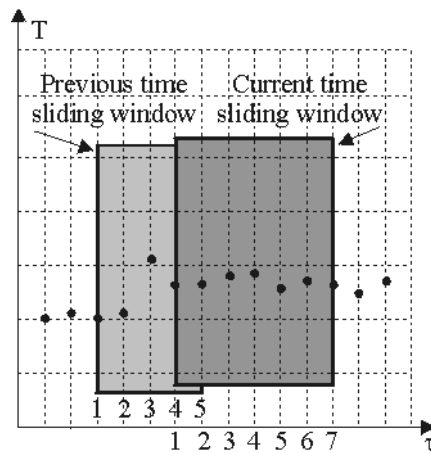


Fig. 1. *Time sliding window*

The length of time sliding window is variable in time and depends on the error, i.e. the difference between the predicted data and the data that are acquired at every time instant. Measuring of time in every sliding window begins from relative time zero. The method of variable length time sliding window includes feedback that corrects the errors in prediction and consequently enables:

1. System fault detection
2. Detection of an accident in the early stage
3. Adaptation of the alarm level
4. Prediction of a system behavior

THE TIME VARIABLE SLIDING WINDOW ALGORITHM

In every time instant two values are significant: The first is the value of acquired data, and the second is the value of the velocity of change of data in time. In that case, the first is the temperature and the second is the gradient of temperature (rate of rise). Because of that, it is important to supervise both values, which means that the algorithm must have two major branches, in other words, there are two models. The first model includes approximation of the front edge of fire alarm signal when the adaptation of the alarm threshold is not necessary. The second model includes threshold adaptation based on the method we propose here. In both cases the false alarm can be detected.

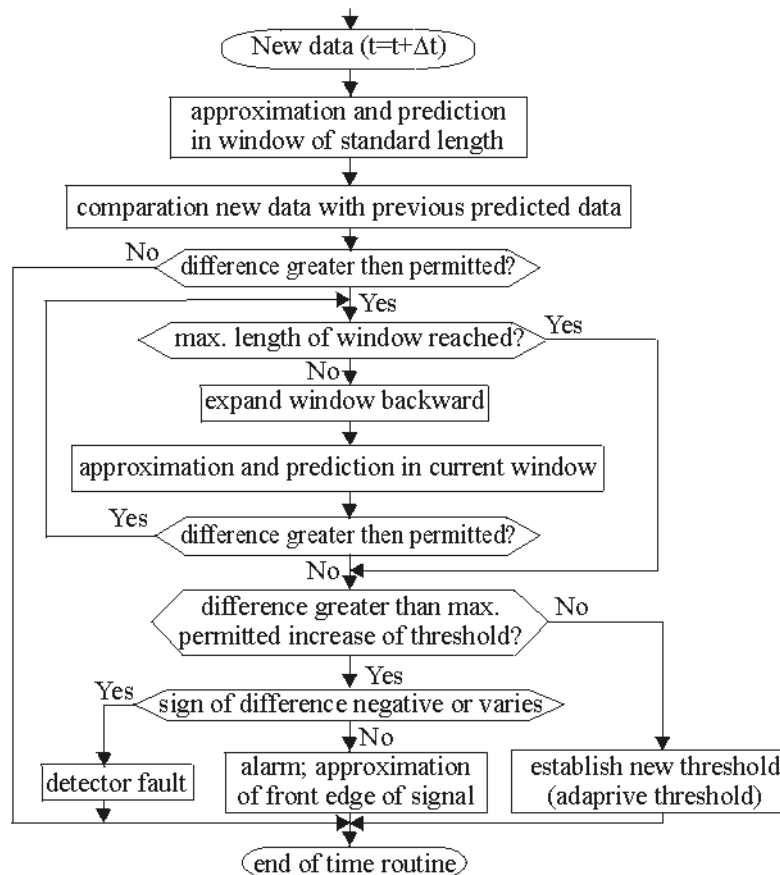


Fig 2. Time sliding window algorithm

The adaptation of the alarm threshold can be applied to the domain in which the two basic criteria are not reached: maximum permitted value of adaptation or critical rate of rise of the signal from the detector.

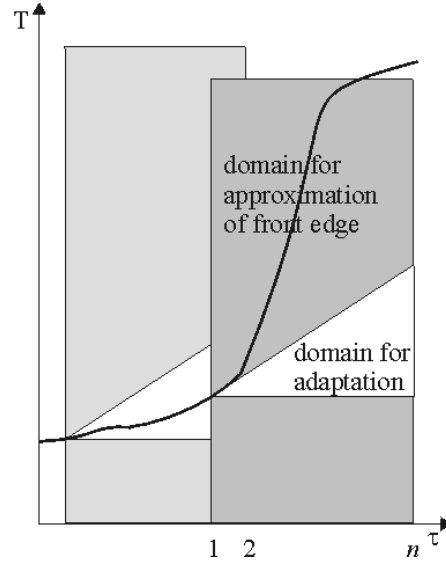


Fig. 3. Domains for approximation

The decision method based on an adaptive threshold employs a threshold changing in time according to the values of the input data and a fixed threshold (see Fig. 4.).

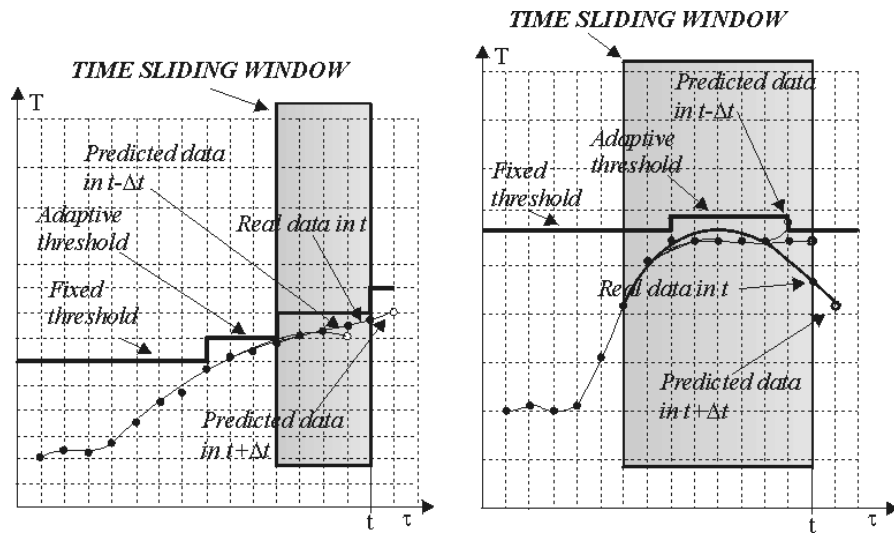


Fig. 4. Adaptive threshold in time sliding window

In fire detection systems where the collecting of data is stationary (polling in equal time distance), the simplest method, which is satisfactorily accurate, is the least squares method with the polynomial approximation of the detected signal. The various types of functions $f(t)$ can be used to approximate the collected fire data. Functions that approximate the time dependent occurrence have m unknown parameters and can be constructed using the weighted residuals method, WRM. Some of the procedures are the least squares method, point matching method, etc. Also, spline polynomials are possible approximation for collected data and approximation of front edge of fire signal with conveniently chosen function.

The first step is to choose the order of polynomial, m , that is equal or less than the number of data in the current window, the time length of which is $\tau = (m-1)\Delta t$, and can be increased as window increase. Discrete time is $K = m$ at the observed moment. From the numerical point of view, the length of the window is $L \geq m$. The left border of window can be calculated as $P = K - L + 1$.

The second step is to choose the appropriate method of fitting the curve (from a variety of WRM or spline) and determine m unknown parameters which, in turn, determine the function for approximation.

The third step is to calculate the value of the function in the next time step.

The fourth step is to estimate the difference between the real and predicted data followed by making a decision.

These steps will be repeated until the mathematical model that describes the real state of the system gives results is not satisfactory accurate. Finally, the only two states of the system are possible: accident or not accident.

THE SMOOTHING SPLINE APPROXIMATION IN TIME SLIDING WINDOW

Spline functions are the category of very useful non analytic functions which consist of different polynomials on segments (and thereby segmental-analytic) linked in specific points which are called nodes. For prediction in time sliding window, in adaptable region, we have used a smooth cubic spline approximation of Schoenberg and Reinch with modification discussed in de Boor [4]. It is a natural cubic spline with knots at all the data abscissas, but it does not interpolate the data (x_i, f_i) . The smoothing spline is unique C2 function, which minimizes

$$\int_a^b S''(x)^2 dx \quad (1)$$

Minimization of (1) establishes a compromise between two conflicting goals:

1. to stay close to the given data, and
2. to obtain a smooth function.

These two conflicting goals may be expressed as

$$\sum_{i=1}^n \left| \frac{S(x_i) - f_i}{w_i} \right|^2 \leq \sigma \quad (2)$$

where w - weights, \square - smoothing parameter, and L - length of time sliding window (number of obtained data in window) in every time instant.

The parameter \square has to be chosen somehow and depends on the weights. In [4] proposes to choose \square somewhere within $\sqrt{2L}$ of L in case $\sqrt{2L}$ is a good estimate for the standard deviation of the data. That is,

$$L - \sqrt{2L} \leq \sigma \leq L + \sqrt{2L} \quad (3)$$

Simply, \square represent a knob which one may set or turn to achieve a satisfactory approximation to the data. More sophisticated choice for \square based on an estimate of the noise in the data obtained by a process called “cross validation”.

In our approach, because of quasistationary nature of fire phenomena, we have defined weights of f_i in window uniformly from 0 to 1, where the data on the right border of the window has $w=1$. On the figure 5 the results of this approach on fictitious (“real” data) are shown.

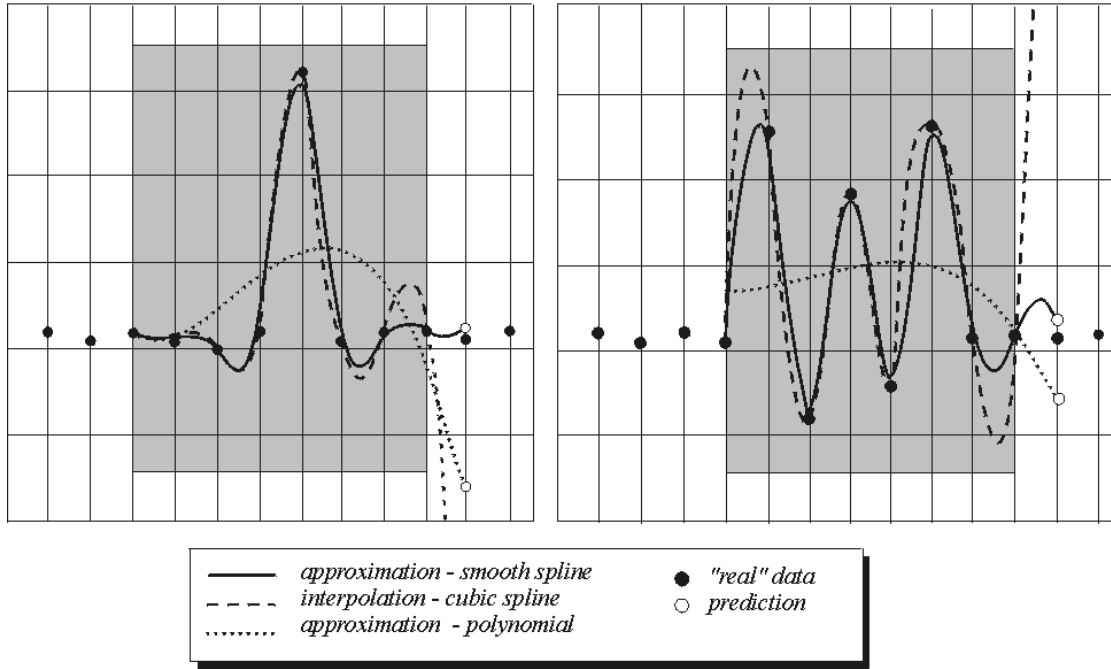


Fig. 5. *Smooth spline approximation in time sliding window*

The most advantage of spline polynomials usage is that this method of prediction is totally independent of time sliding window length. Application of functional analysis described in [6] shows that all comparisons in sense of vector calculus with various lengths of time sliding window, lead to almost identical values of parameters like relative difference, cosine etc.

Spline polynomials as possible approximation for collected data and approximation of front edge of signal with conveniently chosen function built in a simulation software. This software is being developed at the Faculty of Occupational Safety, Department of Fire Detection - Nish. The figure 6. shows a example of experimental data and related approximations in time sliding window.

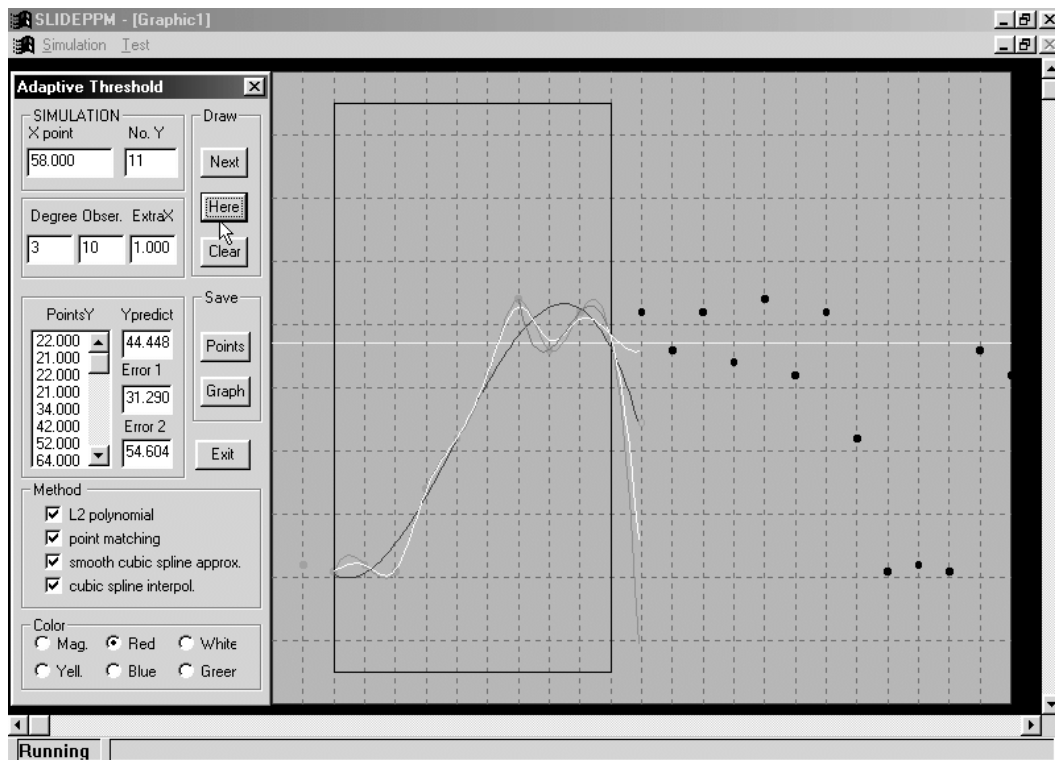


Fig. 6. User interface of simulation software

CONCLUSIONS

The time sliding window method, which is applied for prediction of the development of fire, consists of two basic models. The first model uses a new function for approximation of front edge of fire signal, and the second, which uses smooth spline polynomials for adaptation of the alarm threshold. The method is built in software package for simulation and the first results are promising.

REFERENCES

1. Blagojevich M., Petkovich D.: *Adaptive control and sliding window principle*, International Conference "System Identification and Control Problems - SICPRO 2000", Moscow, 2000.

2. Blagojevich M., Petkovich D.: *An approach to complex safety*, Problemi upravljenja bezopasnostju slozних sistem, Moscow, 1999.
3. Bukowski R., Reneke P.: *New approaches to the interpretation of signals from fire sensors*, Natl. Inst. Stand., MD USA, 1999.
4. de Boor C.: *A practical guide to splines*, Springer-Verlag New York, 1978., 235-243.
5. Forsythe, G.E.: *Generation and use of orthogonal polynomials for fitting data with a digital computer*, SIAM Journal on Applied Mathematics, 5, 74-78., 1957.
6. Peacock R., Reneke P., Davis W., Jones W.: *Quantifying fire model evaluating using functional analysis*, *Fire Safety Journal*, No. 33. 1999.
7. Reneke P., Peatross M., Jones W., Beyler C., Richards R.: *A comparison of CFAST predictions to USCG real-scale fire tests*, Natl. Inst. Stand., MD USA, 2000.
8. Shampine, L.F.: *Discrete least-squares polynomial fits*, *Communications of ACM*, 18, 179-180., 1975.
9. Blagojevich M., Petkovich D.: *New model for approximation of front edge of fire signal*, (will be published).